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John M. Flach

Wright State University - Main Campus, john.flach@wright.edu

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CONTROL WITH AN EYE FOR PERCEPTION: PRECURSORS TO AN ACTIVE PSYCHOPHYSICS

John M. Flach
Wright State University
Dayton, Ohio

ABSTRACT

The perception-action cycle is viewed within the context of research in manual control. A portrait of a perception-action system is derived from the primitives of control theory in order to evaluate the promise of this perspective for what Warren and McMillan (1984) have termed "Active Psychophysics." That is, a study of human performance that does justice to the intimate coupling between perception and action.

INTRODUCTION

Are there important differences between a human actively involved in accomplishing a goal directed activity and a human passively monitoring and making judgements about stimulation imposed from without? In the active mode the subject has control over stimulation. In the passive mode stimulation is controlled by an entity (generally the experimenter) other than the subject. These two modes may be different in terms of the control of attention; in terms of the kinds of information available; in terms of sensitivity to information; and are certainly different in terms of the kinds of activities required of the subject. Certainly Gibson's early studies with touch suggest that active and passive modes are fundamentally different in the kinds of information picked up by the actor/observer (Gibson, 1962). Stappers (1989) has recently shown that active control enhances visual form recognition. Also, research on the effects of automation on the performance of human-machine systems (out-of-the-loop syndrome) suggests that there are fundamental differences between systems where the human functions as a controller compared to systems where the human functions as a monitor (e.g. See Wickens, 1984, P.492). To the extent that the actor and the observer are different, care must be taken with how researchers generalize the results of experimentation. The domination of passive modes of interaction in psychological research (even in ecological research which is based on the concept of the perception-action cycle) may lead to inappropriate generalizations. For this reason a number of people (e.g. Warren & McMillan, 1984) have pointed out the need for research paradigms that permit subjects to actively control stimulation in pursuit of goals. In this paper, a tutorial review of control theory will be presented as one framework within which an "active psychophysics" might be pursued.

INPUT AND OUTPUT

Figure 1 shows a black box representation of a human-environment system. There are two qualitatively different sources of input into this black box and a single output. These inputs and outputs are not single dimensional entities but instead should be considered multidimensional vectors. The distinction between Intention and Disturbance, as qualitatively different inputs to the black box is critical for understanding the behavior of control systems. However, this distinction is often obscured in the literature on manual control. The term input is sometimes used to refer to intention and sometimes to disturbance (Powers, 1978). In general, a good controller will minimize the match between disturbance and output and will maximize the match between intention and output. In other words, a controller will behave so as to accomplish intentions (goals) and will do so in spite of any external disturbances that might perturb the system. The prototypical example is a thermostat. A temperature is input as an intention and this temperature is attained and maintained in spite of external inputs (disturbances) arising as a function of outside temperatures.

A second qualitative distinction is important in characterizing the input signals (both intentions and disturbances). Inputs can be discrete or continuous. An example of a discrete input used in the study of human performance is the Fitts' Law paradigm (see Jagacinski, In Press for review). The appearance of the target is an intentional input in which the goal of the operator is changed instantaneously from one position (the home position) to a second position (the target position). Step tracking is another example in which discrete signals (instantaneous changes of position) are used as inputs. When step tracking is performed in a pursuit mode, as illustrated in Figure 2, then the input is an intention. When step tracking is performed in a compensatory mode, then the input is a disturbance. In discrete control paradigms, dependent measures that are often used include:

Reaction Time – the time from the input signal onset to the onset of the response to that signal. This is illustrated in Figure 2.

Movement Time – the time from the initiation of a response to the input signal to the completion of the response (e.g., target capture).

Accuracy – the match between intention and action (output) at the end of a response sequence.

Submovements – often the output resulting from a discrete input can be parsed into segments (e.g., submovements). Important measures include the number of submovements; the duration of individual submovements; the accuracy of individual submovements; the peak velocities; and the peak accelerations.

Continuous signals can also be used as input to the black box. Typically, the continuous signals used in manual control experiments are constructed as a sum of sine waves. There are two reasons for this choice. First, Fourier's Theorem shows that any periodic signal can be approximated as a sum of sine waves. Thus, sine waves are fundamental building blocks for constructing a wide range of signals. A second reason for using sine waves to construct signals is that for a linear servomechanism a sine wave input will result in a sine wave output at the same frequency, but changed in amplitude and phase. The pattern of amplitude and phase changes can be extremely useful for drawing

inferences about the nature of the black box (e.g., the transfer functions). Also, frequency can be used as a signature to differentiate the sensitivity of the black box to various kinds of inputs. The use of frequency signatures to differentiate sensitivity will be discussed further in a later section of the paper. When continuous signals are input as intentions, then the subject's task is called a pursuit tracking task. In this task the subject sees both a continuously changing target (e.g., a roadway) and a cursor representing her position with respect to the roadway. A good controller would be one that minimized deviations between her position and target position. When continuous signals are input as disturbances, then the subject's task is called a compensatory tracking task. Here the subject's goal is a fixed position (e.g., center of screen or constant altitude) and a disturbance (e.g., windgust) is input that drives the subjects away from their fixed goal. In pursuit tracking, subjects can see movements of the goal and movements of themselves with respect to that goal. In compensatory tracking, subjects see only their own movement with regard to the fixed goal. For research using continuous inputs the dependent variables typically used include:

RMS Error – this is the square root of the sum of squared deviations between cursor (ego or vehicle) position and the goal position (summed over samples) divided by the number of samples. This method of scoring results in a differential weighting of small and large errors.

Small errors contribute proportionally less to RMS error than do large deviations.

RMS Control and RMS Control Velocity – these measures are similar to RMS error. They are indexes of the amount of control activity.

Time-on-Target (TOT) – this is a measure of the proportion of time during a tracking trial that the subject is within the boundaries of the target.

Amplitude and Phase – the amplitude and phase are measured at each frequency of input. The ratio of amplitude in the output to amplitude in the input signal is termed gain. These measurements are important for characterizing the transfer function of the black box.

Remnant – the remnant is the output power at noninput frequencies. This is an index of the control variance that is not correlated with input signals.

NEGATIVE FEEDBACK CONTROL

A simple system that acts to attain and maintain an intention in spite of disturbances is a negative feedback system. Figure 3 shows a simple negative feedback device. The new ingredient that the negative feedback system introduces is error. This is the difference between the intention or goal and the current state of the system. A negative feedback system is driven by error. that is, when error is zero there is no action in this system. When error is non-zero this system will attempt to reduce the error. Whether or not the system is successful in reducing error will depend on the characteristics of \underline{G} . Figure 3 shows a derivation of the relation between Intention, Disturbance, and Output as mediated through \underline{G} . The equation relating these elements is:

$$[G/(1+G)]*Intention + [1/(1+G)]*Disturbance = Output \quad (1)$$

Note from Equation 1 that if G is a simple multiplier then the greater the value of G (i.e., the higher the open loop gain) the closer will be the match between Output and Intention. The term that operates on Intention will go to 1 as G becomes large. The term that operates on Disturbances will go to 0 as G becomes large. Thus, as G becomes large Equation 1 will reduce to:

$$Intention = Output \quad (2)$$

In nature G is never a simple multiplier. For all physical systems there will be a delay associated with G . For control purposes it is not the absolute time associated with this delay but the time relative to the frequency of the signal. That is, the key dimension will be the proportion of a cycle that a signal is delayed. This is termed phase lag. If a signal is delayed by 180 degrees then the negative feedback system will result in a diverging error. Such a system is said to be unstable. For good control G should have high gain when the phase lag is less than 180 degrees. The higher the gain, the faster error will be reduced. G should have low gain, less than 1, as the phase lag approaches and exceeds 180 degrees. This relation between gain and time delay is illustrated in Figure 4, which is adapted from Jagacinski (1977). The graph shows three regions sluggish control, good control, and unstable control. If the time delay is small (small phase lag) and the gain is low then error will be reduced very slowly. An example of a sluggish response to a step input is shown in Figure 4. If the time delay is large and gain is high the error will not be reduced and in fact will become greater. This is the region of unstable control. Pilot induced oscillations in flight result from a pilot responding with too high a gain given the time delays associated with the system. An example of an unstable response to a step input is also shown in Figure 4. If gain is high and time delay is small or if gain is low when time delay is large then good tracking will result. Two examples of the response of a good tracker to a step input are illustrated in Figure 4. Note that as the time delay becomes greater the range of gains that will result in good tracking diminishes.

The relationship between gain and phase lag can also be illustrated using a Bode plot. The Bode plot shows open loop gain (in decibels) and phase lag (in degrees) plotted as a function of the log of frequency (in radians/sec). Figure 5 shows the pattern of gain and phase lag that would be obtained for a good controller. This pattern represents good control in that for those frequencies with phase lag less than 180 degrees gain is high. Thus, intentional signals at those frequencies will be followed closely in the output and disturbances at those frequencies will be filtered out (will not show up as output). In other words, errors will be eliminated quickly. For those frequencies with phase lags greater than 180 degrees gain is less than 1. Thus, the system will be stable. Intentional signals at those frequencies will not be followed in the output and disturbances at those frequencies will not be filtered out (they will be part of the output).

A key landmark in the Bode plot is the "crossover point," the point at which gain is equal to 1 (0 db). For the system to be stable the phase lag must be less than 180 degrees at that point. The distance of the phase lag from 180 degrees is called the phase margin of the system. A positive phase margin is required for stable control. The frequency of the crossover point indicates the bandwidth of the controller. Intentional signals at frequencies below the crossover point will be represented in the output. Intentional signals at frequencies above the crossover point will be filtered out (will be attenuated in the output).

A final point to be noted about negative feedback, closed-loop systems concerns the concept of time. The common sense notions of before and after do not apply. Errors do not precede actions which in turn precede feedback. Errors, action, and feedback are continuously available. In place of the common sense notion of time is the concept of phase. Action can be in-phase with feedback (perception) or out-of-phase. When in-phase the system will be stable. When sufficiently out-of-phase the system will be unstable.

MANUAL CONTROL

Manual control is the study of negative feedback control systems in which the loop is closed through a human operator. That is, the human operator is given a task or goal to accomplish this goal is accomplished by observing displays and manipulating controls. This situation is illustrated in Figure 6. Note that the G in the forward loop of Figure 4 has been replaced by two boxes in the forward loop of Figure 6. One box, labelled Controller, represents the transfer function for the human operator. The second box, labelled Plant, represents the transfer function for the physical system that the human is interacting with (e.g., dynamics of the helicopter). The central problem for a theory of manual control has been to build a model or theory of the human operator. Two approaches to modeling the human will be distinguished. One approach assumes that the human operator responds continuously to error. The second approach assumes that the human responds in a discrete fashion.

Continuous Control

Early researchers began with the assumption that the transfer function of the human operator would be invariant, independent of the plant dynamics. It was assumed, that once this transfer function was discovered it could be used to predict performance across a wide range of plant dynamics. McRuer and his colleagues (e.g., McRuer & Jex, 1967; McRuer & Krendel, 1974; McRuer & Weir, 1969) soon discovered that this definitely was not the case. As the dynamics of the plant changed, so too, did the describing function for the human operator. The invariant, as McRuer et al. discovered was not at the level of the human but was at the level of the total forward loop (human + plant) describing function. This invariant at the level of the human/plant combination was the basis for the classic "crossover" model. The key insight behind the crossover model is illustrated in Figure 7. The first column in Figure 1 shows Bode diagrams and transfer functions [using Laplace notation] for three simple plant dynamics. The second column in Figure 7 shows describing functions obtained for humans controlling each of the three dynamic plants. The final column shows the describing function for the human/plant combination. Note that the patterns in Column 3 are invariant and that they have the same form as the "good" controller illustrated in Figure 5. What was surprising to earlier researchers should be obvious in retrospect. The constraints on good stable performance operate at the level of the total forward loop (human + plant). To do the task the human must operate within those constraints and therefore must adapt to the plant dynamics in a way that is consistent with those constraints. Thus, the "crossover" model predicts that in the region of crossover the human plus the plant will approximate the transfer function shown in Column 3 of Figure 7.

In adjusting to the plant dynamics to both satisfy the demands to minimize RMS error and to satisfy the constraints for stability the human behaves like an optimal controller. This observation

was the basis for the “optimal control” model of the human operator (e.g. Baron & Kleinman, 1969; Kleinman, Baron, & Levison, 1970; Kleinman, Baron, & Levison, 1971). The optimal control model assumes that the human operator uses an internal (mental) model of the plant dynamics to estimate the current states of the system from delayed, noisy observations of display position and velocity. The human responses to these states are based on an optimal control law which chooses response gains that minimizes a linear combination of squared tracking error and squared control velocity. Thus, in a sense, the model assumes that the operator attempts to achieve minimum error with minimum effort. These responses are filtered through the limb dynamics and are contaminated by motor noise.

The optimal control model has been popular because there is a natural mapping from the elements of the model to the stages (encoding, estimation, decision, response) of the standard information processing model that has dominated modern psychology (See Pew & Baron, 1978). The optimal control model also provides a better fit over a wider range of frequencies to human performance data than does the crossover model. However, to do so it requires a greater number of parameters.

The crossover model and the optimal control model both assume that the human responds in a continuous, proportional (linear) fashion to error and error velocity. However, there is much evidence that the human is not linear (e.g. see Knoop, 1978). For example, there is the presence of remnant in the human control response. Remnant is power at output frequencies not present in the input. As noted in an earlier section, a linear system would only have output at the input frequencies. The optimal control model accounts for the remnant by assuming the presence of broad band white noise injected by human perceptual and motor processes. The non-white shape of the measured remnant is thought to reflect the dynamics of the humans’ perceptual and motor processes. Others have argued that the remnant arises, at least in part, due to the discrete, nonlinear nature of the human transfer function.

Discrete Control

In discussing discrete control models of the human operator three classes of models will be presented—synchronous discrete controllers, asynchronous discrete controllers, and hierarchical controllers.

Bekey (1962) lists a number of studies that have found evidence of a “psychological refractory” period when a human is required to respond to discrete stimuli spaced by less than about 0.5 seconds (Hick, 1948; Welford, 1952; Davies, 1957). One inference that might be drawn from this finding is that the human “acts on discrete samples of information from the external world.” Figure 8, adapted from Bekey (1962) gives examples of two synchronous discrete controllers. These controllers act on discrete observations taken at a fixed frequency. A synchronous sampler with a 0-order hold responds as a function of the position observed at each sample. The synchronous sampler with a 1st-order hold responds as a function of the position and velocity observed at each sample. Three important attributes of synchronous discrete controllers noted by Bekey (1962) are:

- (1) Changes in the input cannot have any effect until the next sampling instant occurs.

(2) The presence of the sampler limits the frequencies which can be reconstructed at its output to those not exceeding one-half the sampling frequency.

(3) The action of the sampler generates harmonics in the output which extend over the entire frequency spectrum, even when the input is band limited. (Bekey, p. 45-46.)

The last attribute provides an alternative explanation for the remnant power routinely observed in human tracking data.

A synchronous discrete controller responds at a fixed frequency. An asynchronous controller responds at irregular intervals. Angel & Bekey (1968) have proposed a finite-state model for manual control that behaves asynchronously. The logic of the finite-state controller is illustrated in Figure 9. Inputs to this controller are coarsely quantized with regard to threshold boundaries on position and velocity. These boundaries are the dashed lines in Figure 9a. These quantized inputs are responded to with simple force time programs which are shown in each region of state space. For example a large position error with low velocity evokes a large amplitude bang-bang response. This type of model has great intuitive appeal for modeling human control of second-order control systems, where there is evidence that humans exhibit bang-bang control (Young & Meiry, 1965). This nonlinear style of control provides still another alternative explanation for remnant.

Costello (1968) proposed a model of the human tracker using a hierarchical control model. Costello's model is illustrated in Figure 9b. Costello proposed two modes of control. He proposed that the human controller responded to small errors and error velocities in a manner consistent with the crossover model. This is the central region of the state space identified with the constant coefficient mode. To large errors, the model predicts that the human will respond in a time optimal bang-bang fashion. Costello called this the surge mode. Jagacinski, Plamondon, and Miller (1987) have also employed a multi-level style of modeling in which a number of low level motion generators (Herdin mode, predictive mode, close following mode, fast acquisition mode) are combined with finite state logic to model human performance in capturing evasive, moving targets.

SUMMARY

The continuous control models have dominated much of the work on manual control. These models have been useful tools for evaluating human control systems and for making predictions about stability of these systems. They have particularly been widely used for studying vehicular control. However, it is clear that some of the assumptions made by these models must be questioned. One must wonder whether the practical utility and success of these models has retarded scientific progress in understanding human control.

There is one intervening variable that should be considered when choosing between the linear, proportional control models (i.e., crossover, optimal control, synchronous controller) and the nonlinear, discrete control models (i.e. asynchronous or hierarchical controllers). That is the time lag of the physical system being controlled. The linear, proportional control models work well for systems that have small time lags (e.g., high performance aircraft). However, these types of models are totally

inadequate for systems with long time lags such as thermodynamic systems (see Crossman & Cooke, 1974). For slow responding systems it is clear that humans respond in a discrete, nonproportional fashion.

This has been a very brief and selective review of some of the models that have been proposed for the human controller. For the most part, the research that has inspired these models has employed simple laboratory tracking tasks using moving cursors on CRT displays. In this kind of task the error signal is clearly defined and thus the perceptual problems have not generated very interesting problems. It remains for an ecological psychology to study control behavior with less well defined error displays (e.g., optical flow fields). This review is presented here because as the perceptual problems are addressed, our ability to draw correct inferences about perception will depend on our use of informed assumptions about action.

Closing the Loop Through the Optic Array

“...instead of searching for mechanisms in the environment that turn organisms into trivial machines, we have to find the mechanism within the organisms that enable them to turn their environment into a trivial machine.” (von Foerster, 1984, p. 171)

The laboratory tracking task, in one sense, is a task that turns humans into a trivial machine (e.g. a simple gain, integrator, or differentiators). The error signal and the goal of the operator are “trivial” relative to the signals by which humans control their own locomotion. The problem in more natural environments is not simply to generate the appropriate control law, but to extract from the “booming, buzzing confusion” the information that specify the goals and the error with respect to those goals. Gavan Lintern (personal communication) has observed that, when learning to fly, controlling the airplane (getting it where you wanted it) was not the problem. The problem was knowing where you wanted to be. That is knowing what the correct glideslope looked like. A critical aspect of the organism turning its environment into a trivial machine may be an ability to pick-up information about regularities in the environment. Thus, it is the tuning to invariants in perceptual arrays that allows the “booming, buzzing confusion” to be managed. How information (i.e. invariants, constraints, or structure) in the optic array supports action has been a central question for ecological psychology ever since Gibson, Olum, and Rosenblatt’s (1955) classic analysis of parallax and perspective during aircraft landings. However, in asking questions about the pick-up of information from optic arrays there is little evidence of a commitment to “active vision.” Many of the studies of information pick-up have employed passive psychophysical methodologies (e.g., Warren, 1976; Owen, Warren, Jensen, Mangold, and Hettinger, 1981; Cutting, 1986; Anderson and Braunstein, 1985; Warren, Morris and Kalish, 1988; Larish and Flach, in press). Not only have our experiments employed passive tasks, but Stappers, Smets, and Overbeeke (1989) have argued that our conceptualizations of the flow field and of the information within it have been founded on the image of a passively translating, disembodied eye. They argue that many of the classic ambiguities disappear when one considers the information in optic flow fields generated by bouncing eyes locomoting over a surface of support. Stappers, et al. note that formal accounts of optic flow (e.g. Longuet-Higgins and Prazdny, 1980; Koenderink, 1986) “neglect the fact that the optic flow is largely brought about by the actions of the observer, and for just this reason it can be relative to the observer’s effectivities: the observer’s actions scale the information he samples.”

The Performatory Loop

Figure 10 illustrates an initial framework for asking questions about the perception-action cycle where the loop is closed through an optic array. In this framework, the human observer is given an implicit (e.g. maintain stable posture) or explicit (e.g. maintain a constant altitude) goal. Control activity is then measured as a function of manipulations of the optic array (e.g. front vs. side view, lamellar vs. radial flow, parallel vs. perpendicular texture). A number of studies have begun to appear that have been framed in this manner. Stoffregen (1985) and Andersen and Dyer (1989) have used postural regulation as a control problem within which to study optic flow. Owen and Warren (1987) report research that examined control responses to discrete changes in acceleration and to ramp changes in altitude in order to identify the optical information that specifies egospeed and altitude. Warren (1988) review a series of studies that have examined altitude control with a continuous, sum-of-sines disturbance. Within this framework, Warren has varied the nature of the optic array (e.g. presence of perspective roadway) and the nature of the task (e.g. altitude maintenance, or fly as low as possible) in order to isolate the functional optical information for altitude. Johnson, Bennett, O'Donnell, and Phatak (1988) have also used an altitude regulation task to examine the utility of alternative structures in the optic array.

The Johnson et al. paper is particularly useful for illustrating the promise of control theoretic methodologies for supporting inferences about perception and action. In order to highlight the logic of the control methodologies the details of the experiment will be greatly simplified. Johnson et al. were interested in comparing the relative efficacy of two sources of optical information about altitude—splay angle and optical density. To address this question displays were chosen which isolate the two sources of information. These are shown in Figure 11a. Texture parallel to the direction of travel contains splay. Texture perpendicular to the direction of travel contains optical density but no splay. Square texture combines both splay and optical density. Crossed with the type of display were three types of disturbance. A horizontal disturbance (altitude) affected both parallel (splay) and perpendicular (optical density) texture. A fore-aft disturbance (headwind) affected only perpendicular texture. Finally, a lateral (side-to-side) disturbance affected only parallel texture. The three disturbances were constructed from sine waves so that the bandwidths of the disturbances were similar, but so that the frequencies were specific to a disturbance (no shared harmonics). This is illustrated in Figure 11b. Frequency can now be used as a signature to identify the control activity specific to optical features. Johnson et al. found better control of altitude with perpendicular texture. They also found that there was more altitude control resulting from the fore-aft disturbance (seen only in perpendicular texture), than from the lateral disturbance. This provides strong evidence that for the hover task studied, perpendicular texture provided a powerful source of information, guiding altitude control behavior whether it was specific to altitude or not.

Exploratory Behavior

The framework in Figure 10 represents an advance over passive psychophysics. However, experiments designed within that framework, still constrain the human to behave as a rather simple machine (servomechanism). In the framework of Figure 10 behavior arises only as a function of error with respect to performatory goals. However, humans act, not only to accomplish performatory goals, but also, humans act to pick-up information. Humans actively explore the environment. This exploratory mode of behavior is intimately coupled with performatory modes of behavior.

Information picked-up through exploratory activity will often support performatory activity. Also, performatory activity will itself result in the pick-up of information. An important challenge for an active psychophysics will be the study of the coupling of performance with exploration. Experimental paradigms must include tasks that allow or even encourage exploration. Active psychophysics must explore measurement and analysis techniques for parsing exploratory and performatory activities; or must discover meaningful higher-order parameters for gauging the interaction of exploratory and performatory modes.

One basis for parsing exploratory and performatory activities might be the distinction between correlated and uncorrelated power resulting from frequency analyses of control behaviors. For systems with small time constants and for well trained operators it might be expected that performatory activities will be closely linked to the "driving function" (i.e., the changing goal or the disturbance that perturbs the system from a fixed goal). Thus, performatory activity will be task driven. Exploratory activity, however, originates with the operator. This will likely be uncorrelated with the driving function and therefore, will appear as remnant. As we have seen earlier in this paper exploratory activity will probably not be the only source of remnant. Other sources that have been considered include perceptual/motor noise, discrete response strategies, nonlinearities, and uncorrelated optical activity. Remnant appears to be rich in information about the human operator. In fact, it could be argued that most of the psychology resides in the remnant. Whereas the correlated power carries little information about the operator, informing us, rather about the task.

Higher order parameters for gauging the interaction of performatory and exploratory modes might be stability and bandwidth. As operators discover more effective ways to pick-up information, this should be reflected in either larger stability margins or in greater bandwidths.

Questions about remnant may be the only avenue for addressing the performatory/exploratory distinction within the experimental framework shown in Figure 10. In this framework there is only a single response channel for both exploratory and performatory activities. Frequency analysis is a useful tool for partitioning different signals within a single channel. It may be easier to study performatory/exploratory interactions if our experimental framework is expanded to permit a second channel of activity. A natural choice for this second channel of activity would be eye movements as shown in Figure 12.

While it is not impossible to imagine situations where eye movements can have a performatory function (e.g., social interactions), in many natural task situations eye movements are purely exploratory. That is, they have no direct effect on error with respect to performatory goals. The indirect effects, however, may be great in terms of the information pick-up that the eye movements mediate. For this reason, the study of eye movements must be a critical element within an active psychophysics.

When the possibility of eye movements is introduced an important theoretical question must be addressed. This involves the question of whether information is specific to an ambient optic array or to the retinal array. For example, the focus of expansion (Gibson, 1947; 1950; 1958; see also Warren, Morris, and Kalish, 1988) is an invariant that specifies the direction of locomotion which has been defined relative to the ambient optic array. That is, the focus of expansion is a pattern within optic flow that arises as a consequence of a moving observation point. This pattern is a

consequence of ecological optics—the properties of light. It is independent of the nature of a sensory mechanism (e.g. simple vs multifaceted lens) and is independent of the viewport (i.e., where the organism is looking). On the other hand, Cutting's (1986) differential motion parallax has been proposed as an alternative invariant specifying direction of locomotion that has been defined with respect to the retinal array. That is, the invariant relations of differential motion parallax are specific to a viewpoint. They depend on a particular point of fixation.

I assert that both the ambient optic array and the retinal array descriptions have an important place in an active psychophysics. The world (including the observer) structures the ambient array. The structure in the ambient array is information about the world and the observer. This structure is present at a station point and in the relations between station points. Pick-up of information requires first a transducer sensitive to the energy that carries the structure. Second, pick-up depends upon activity (sampling). What information is picked up depends on the activity of the observer? A stationary observer can pick up only the information at a single station point. This is an extremely impoverished view. A moving observer has access to information from multiple station points and has access to the information in the relations across station points. Note that no information about environmental layout is created by movement. The information exists whether the observer moves or not. Movement simply makes the information available. Also note, that a particular movement only provides access to the information at the station points sampled and in the relations across those station points. Some ways of acting will reveal different information than others. Therefore, some ways of acting will be more effective for certain tasks, because the information made available will be more appropriate.

An important challenge for an active psychophysics will be to provide a framework for evaluating the effectiveness of sampling behavior. The challenge is not to provide an absolute metric for effectiveness, because effectiveness can only be measured relative to a task, but to provide a collection of methodologies for asking questions and drawing inferences with regard to sampling behavior. Thus, it is meaningful and important to ask the following question: For a given pattern of sampling behavior what information is in principle available to the actor/observer? This is where the retinal array becomes important. The retinal array is one kind of record of the information made available by a particular pattern of sampling behavior.

Mathematical descriptions of the retinal array can be very useful for generating hypotheses about what subset of the information from the ambient array is preserved over a particular set of samples from that array. However, it is important to note that there is an asymmetry in the logic of mathematical descriptions of both the ambient field and the retinal field. If an invariant mathematical relationship can be demonstrated between structure in the ambient array (or structure on the retina) and properties of the world (including observer) then this is proof that information is present. However, failure to discover a mathematical relationship does not prove that there is no structure. In this sense, no particular form of mathematical representation is privileged.

An active psychophysics must appreciate the importance of mathematical analyses of the ambient array and of the retinal array. However, it should never be constrained by these analyses. These mathematical analyses will help us to discover what are interesting questions to ask. However, the answers can only come from observations of behavior.

For an active psychophysics to be complete, observations must be made in which the actor has unrestricted and independent control over performatory and exploratory modes of behavior. In all of the studies cited above that examined control through optic arrays, performatory and exploratory behavior were constrained so that the actor could only look where he was going. However, in most natural environments no such restriction is present. When given independent control of exploratory behavior, where do people look? Are some patterns of looking more or less effective than others? Do different patterns of looking result in qualitatively different styles of control? These are the kinds of questions that motivated Gibson's (1962) observations on active touch (see also Stappers, 1989). These kinds of questions must be central to an active psychophysics.

Adaptation and Learning

Adaptation and learning are obvious and important side effects of the interaction between performatory and exploratory modes of behavior. Exploratory activity results in the discovery of information. The more information available to the actor the greater will be the number of control strategies that are available. A wider range of control strategies will open the possibility for both greater precision of control and greater stability. Figure 13 shows the addition of "adaptive logic" to our growing diagram of a perception/action cycle. Behind this small box hides enough mysteries to support many careers in Psychology.

The signals entering the adaptive logic box are of the same general nature as the signals throughout the network. These signals are patterns of energy in space-time and these signals are operated on by the boxes in the diagram. However, the signals leaving the adaptive logic box are different. They represent operators that operate on the other boxes. For example, output from the adaptive logic box may result in a change of the transfer function between observation of error and action. This results in an interesting circularity or coupling. The patterns of energy in space-time (connections between boxes) are both operators and operands. So too, the embodied constraints represented as boxes are themselves operated on by the very signals upon which they operate. This kind of coupling between system and signal is also seen in neural nets and connectionist machines that tune to invariants in stimulation (see McClelland and Rumelhart (1986) for review).

Control theoretic technologies may not be the most useful tools for organizing our thinking with regard to this coupling of system and signal. Field descriptions such as those described by Kugler and Turvey (1987) may be more useful. However, as we explore new modes of description we should proceed armed with the intuitions of those who have gone before. McRuer, Allen, Weir, and Klein (1977) have proposed the Successive Organization of Perception (SOP) model as a tool for understanding how the control logic might change with learning. This model, shown in Figure 14, includes three modes of tracking. The compensatory mode has been discussed throughout this paper. In this mode the human acts like a servomechanism responding to error between intention and output. The compensatory mode would dominate for a naive operator. As the operator becomes experienced he begins to learn the dynamics of the plant being control. Thus, he can anticipate the response of the plant. This allows him to respond directly to intentions rather than to error. To the extent that his anticipations are incorrect the residual error will be reduced as a result of the inner compensatory loop. If the environment that specifies the intention behaves in a consistent way (e.g. a track composed of a single sine wave), then the observer may tune to these consistencies. In other words, the operator may learn the "rule" or "pattern" that governs the input. This will allow a response to the

higher order pattern and free the operator from the requirement to continuously monitor input or error. This mode has been called precognitive. For example, an operator tracking a cursor driven by a single sine wave, may synchronize his response to the periodic pattern. Thus, the operator could close his eyes and still maintain close tracking (at least for short periods). While one mode or the other may dominate, depending on the state of the operator (e.g. experience level) or the state of the task (e.g. regularity), all modes are expected to operate in concert complementing each other.

Important empirical work has also been done on adaptation in the context of manual control (e.g. Young, 1969; Wicken, 1984). This empirical work should be instructive to those pursuing an active psychophysics. The following challenge from Young (1969) signifies the need for an active psychophysics to organize our thinking with regard to adaptive control.

"...what is being offered to solve the manual control problems of tomorrow? What will be the "critical task" facing the astronaut entering the atmospheres of a strange planet, the captain of an SST, the pilot of a commercial airliner making an approach in zero-zero visibility, the VTOL pilot guiding his unstable vehicle to a downtown landing field, the submarine commander, or the engineer on a high speed transportation system? Will they be involved in compensatory tracking? Obviously not. They will be on board for the versatility, adaptability, and reliability they add to an automatic system. They will be expected to observe the environment and use "programmed adaptive control" to change plans. They will monitor instruments and repair malfunctioning components. They will control in parallel with the automatic system and take over in the event of failure. What is the extent of the theory for predicting man-machine behavior in these simulations? It is almost nil." (Young, 1969, p. 329)

CONCLUSIONS

"The world is as many ways as it can be truly described, seen, pictured, etc. and there is no such thing as the way the world is." Nelson Goodman (1968)

Figure 13 represents one way to picture a perception/action cycle. It is not the way to picture perception/action cycles. The representation is not a roadmap for the future. In fact, it could be argued that if the representation in Figure 13 is taken too literally, then it will severely constrain our thinking and will be an obstacle to future progress. If the representation in Figure 13 is useful it is as a map to the past. That is, as a link to the study of manual control. The research on manual control has much to offer to anyone interested in the coupling of perception and action. As a new active psychophysics is molded, its shape should not be constrained by the cybernetic hypotheses that guided much of the work in manual control. However, our vision of the future of active psychophysics will be much clearer if we stand on the shoulders of those who have gone before. The methodologies of manual control offer an important alternative to the passive methodologies that dominate current psychophysics. If these methodologies are applied with caution and restraint, the future of an active psychophysics will hold great promise. Alternatively, the challenges posed by an ecological approach to perception and action promise to rejuvenate an area of research that is being lulled to sleep reliving past successes.

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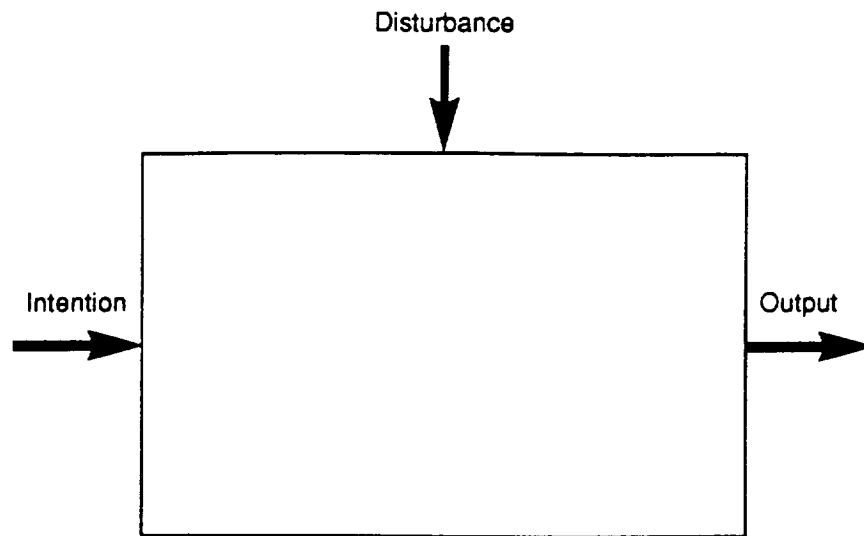


Figure 1. A black box representation of a human-environment system.

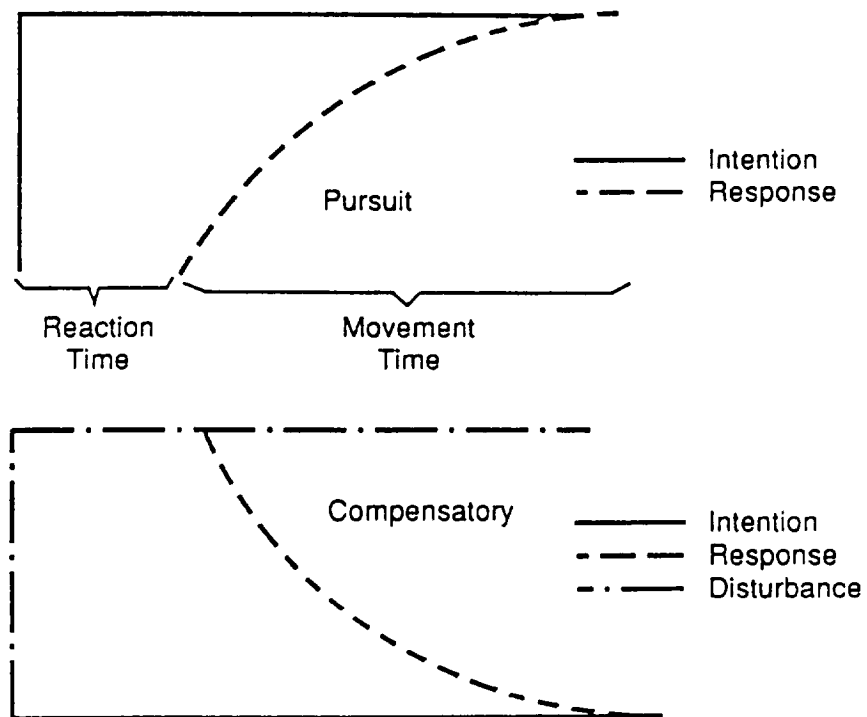
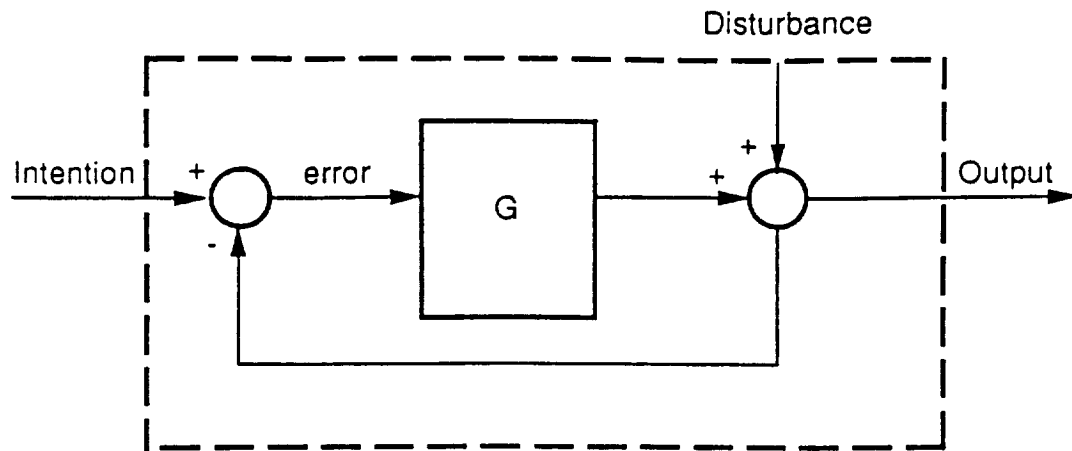


Figure 2. Responses to a step input on the intention channel (pursuit) and on the disturbance channel (compensatory).

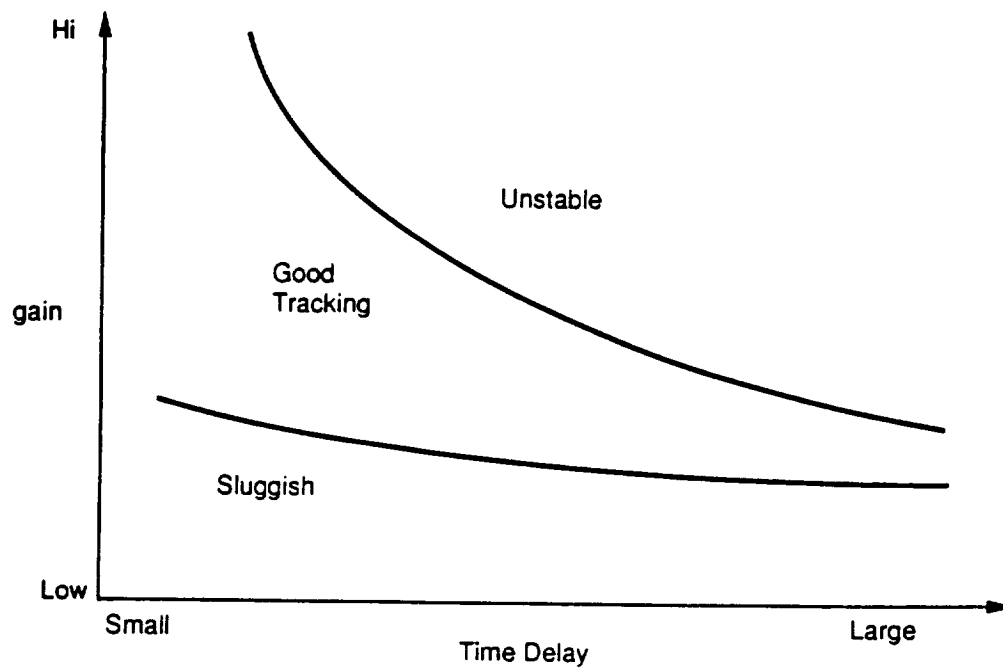


$$\begin{aligned} \text{error} &= \text{Intention} - \text{Output} \\ G * \text{error} + \text{Disturbance} &= \text{Output} \end{aligned}$$

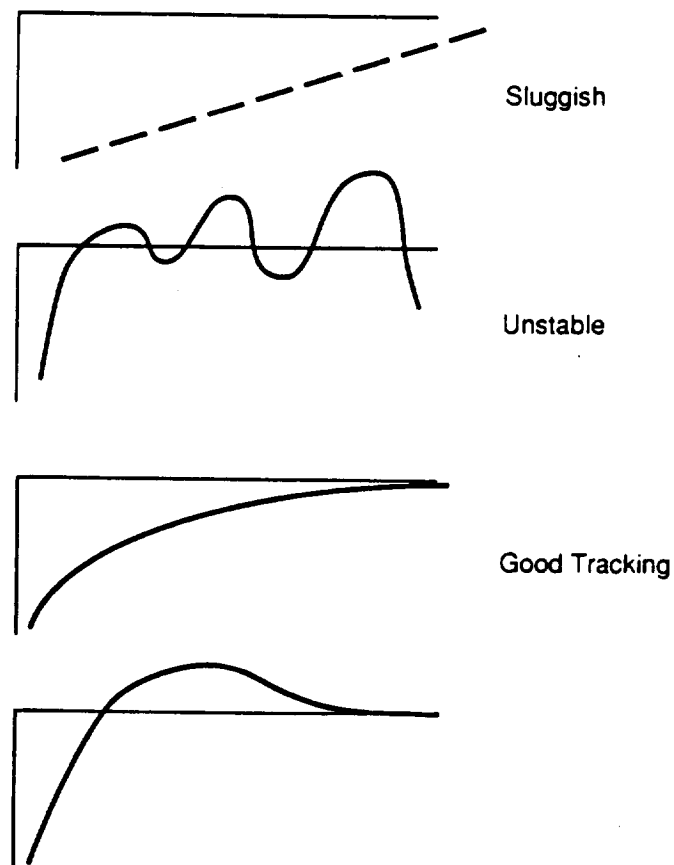
$$\begin{aligned} G(I - O) + D &= O \\ GI - GO + D &= O \\ GI + D &= O + GO \\ GI + D &= O(1 + G) \end{aligned}$$

$$\left[\frac{G}{1 + G} \right] \text{Intention} + \frac{1}{1 + G} \text{Disturbance} = \text{Output}$$

Figure 3. A simple negative feedback system.



(a)



(b)

Figure 4. (A) Illustrates tracking quality as a function of gain (sensitivity to error) and the time delay (delay of feedback) (Adapted from Jagacinski, 1977) (B) Illustrates responses to step inputs for the regions shown in A.

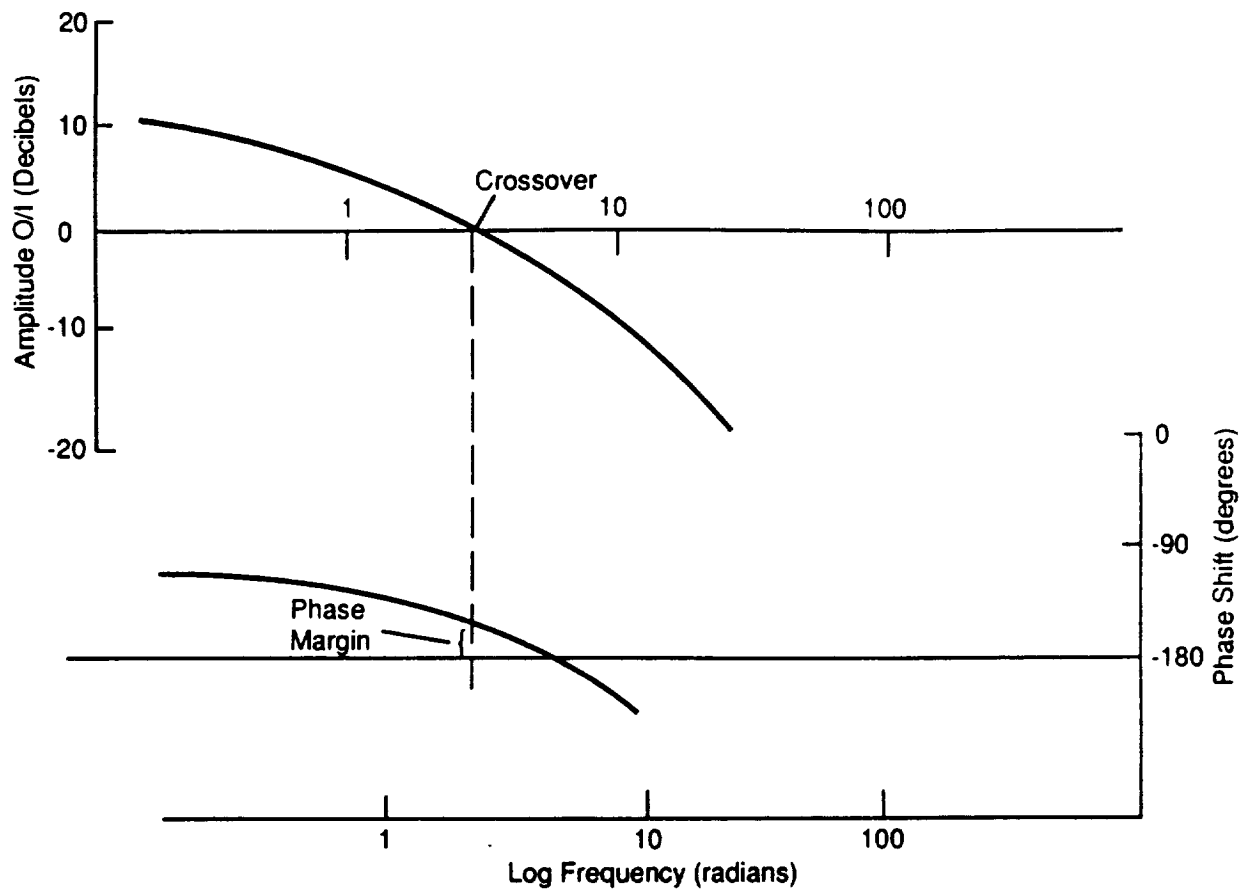


Figure 5. A Bode plot typical of a “good” controller.

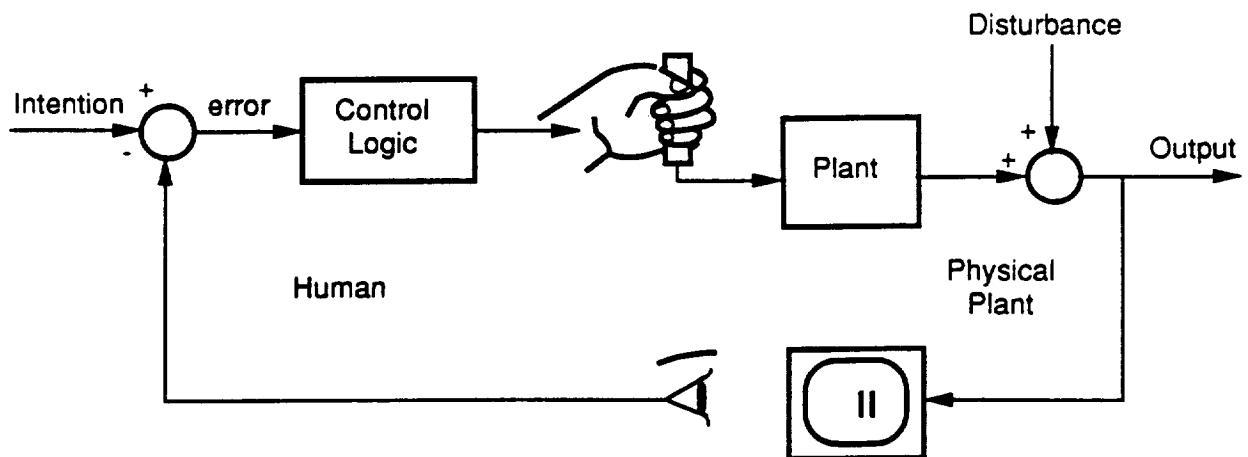


Figure 6. The manual control framework.

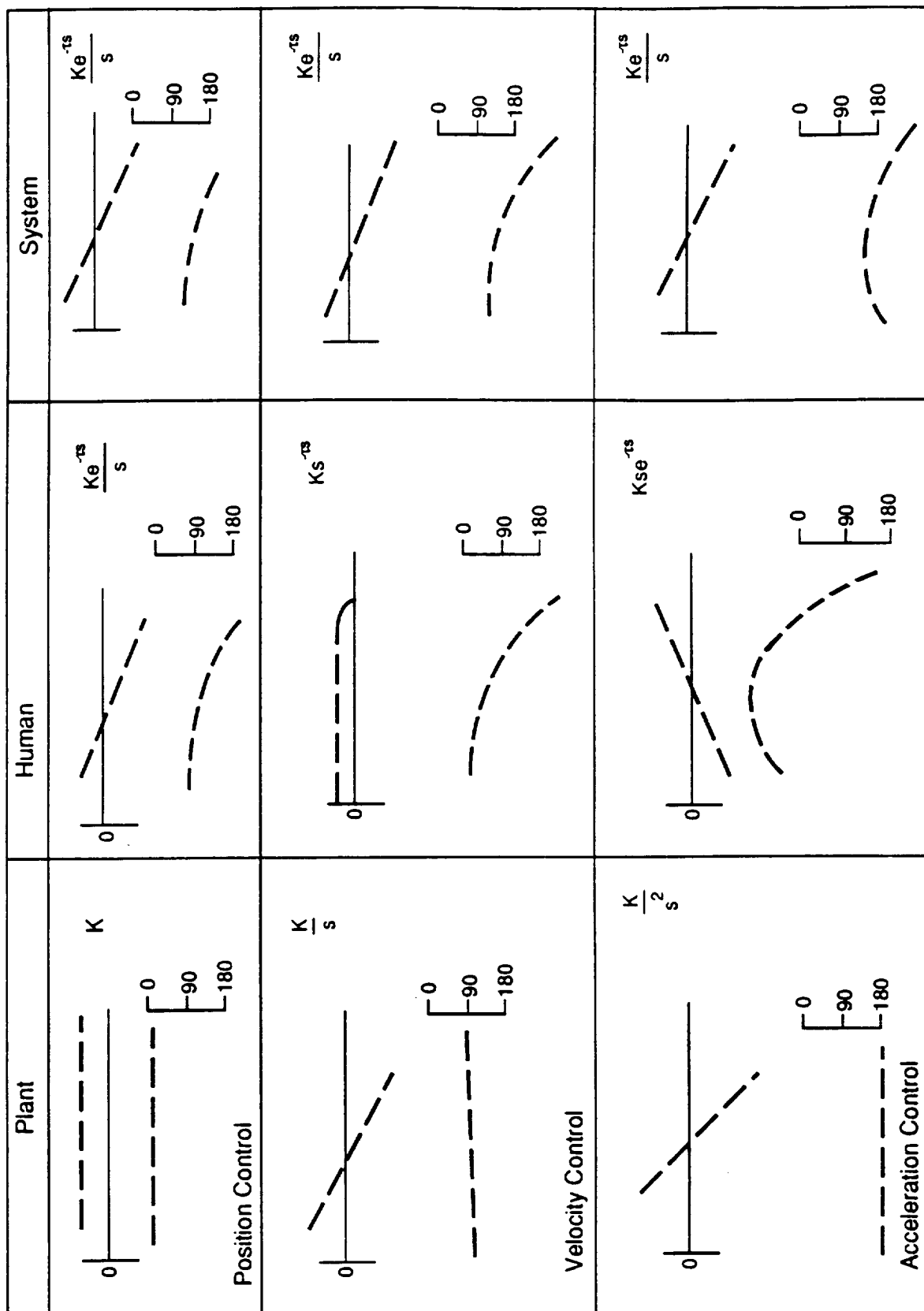


Figure 7. An illustration of the logic behind the crossover model. Shows how the human adapts to the demands imposed by three simple plants.

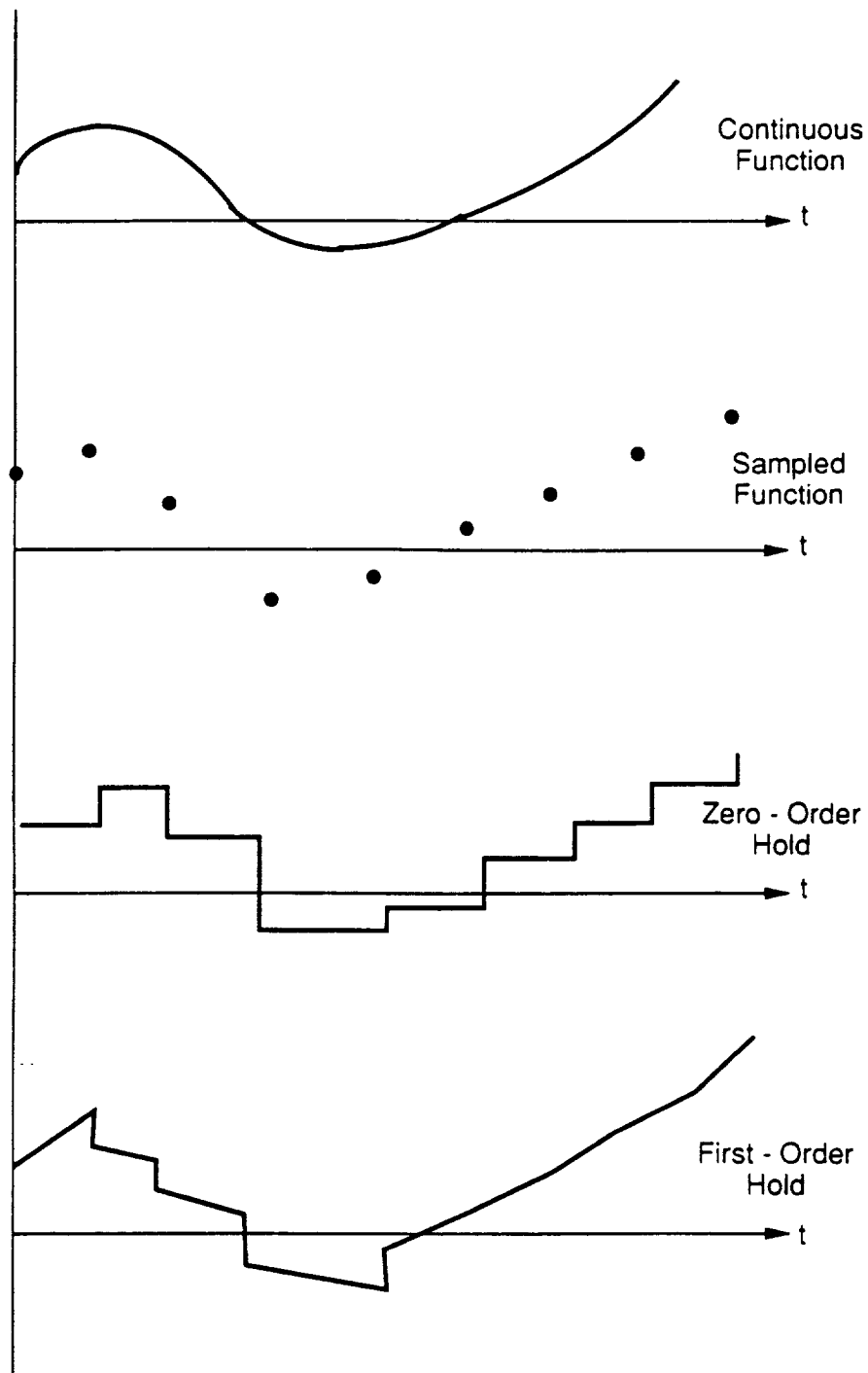


Figure 8. Two strategies for discrete synchronous control. Zero-order extrapolates based on position. First-order extrapolates based on position and velocity (Adapted from Bekey, 1962).

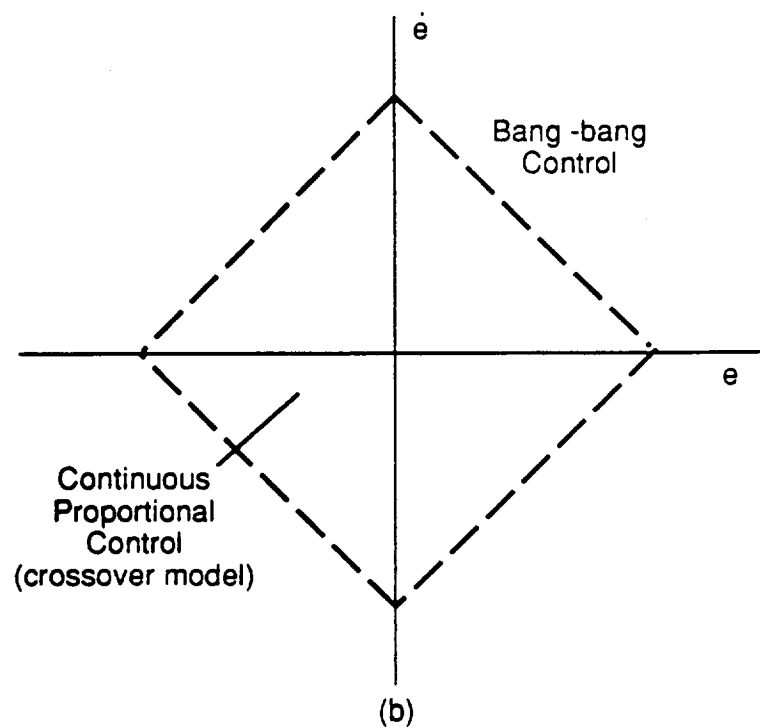
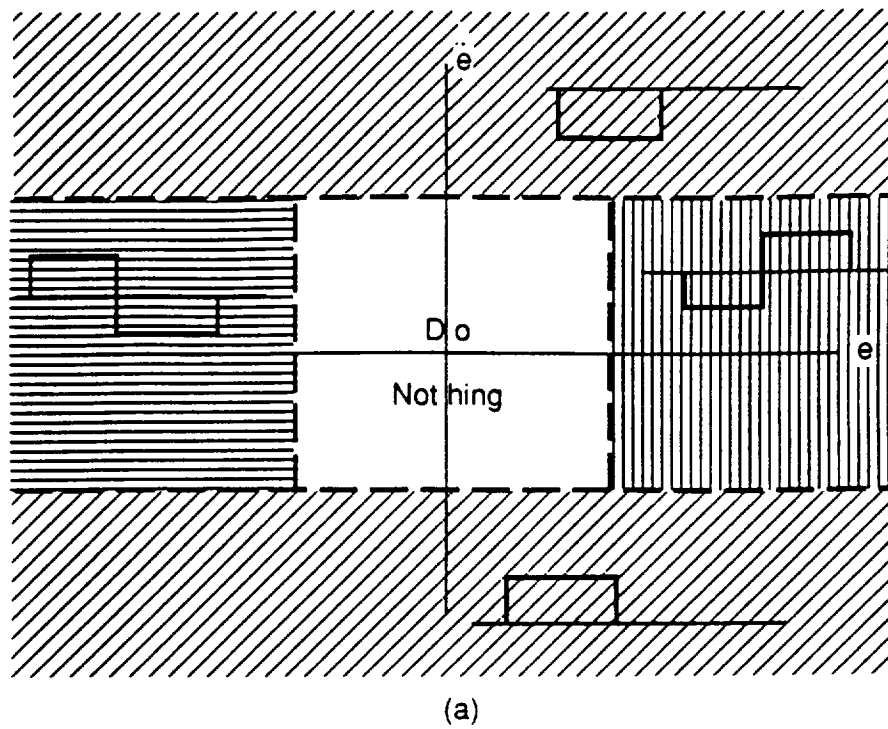


Figure 9. (A) Logic for an asynchronous discrete controller proposed by Angel and Bekey (1968)
 (B) Logic for hierarchical "surge" model proposed by Costello (1968).

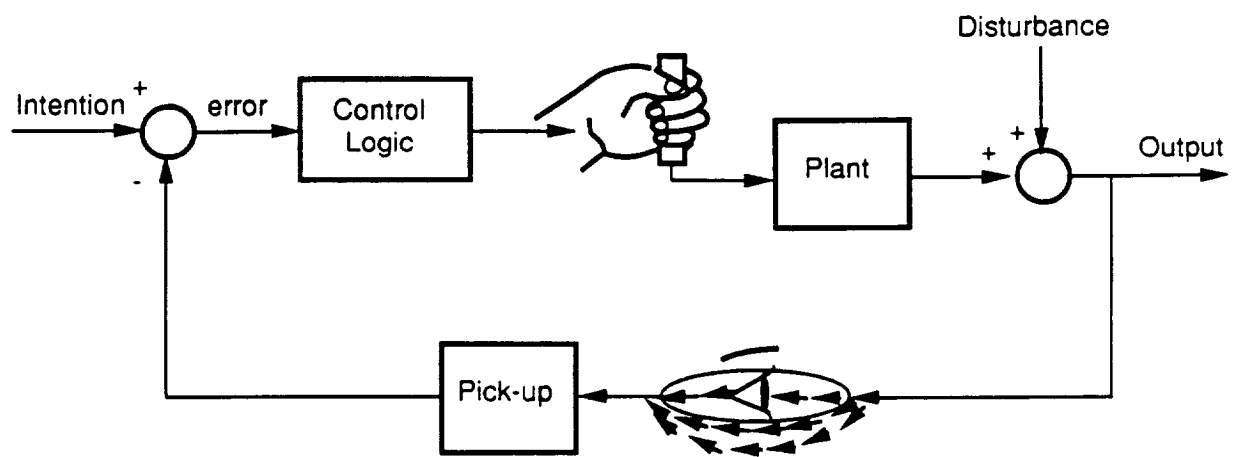


Figure 10. Closing the loop through the optic array.

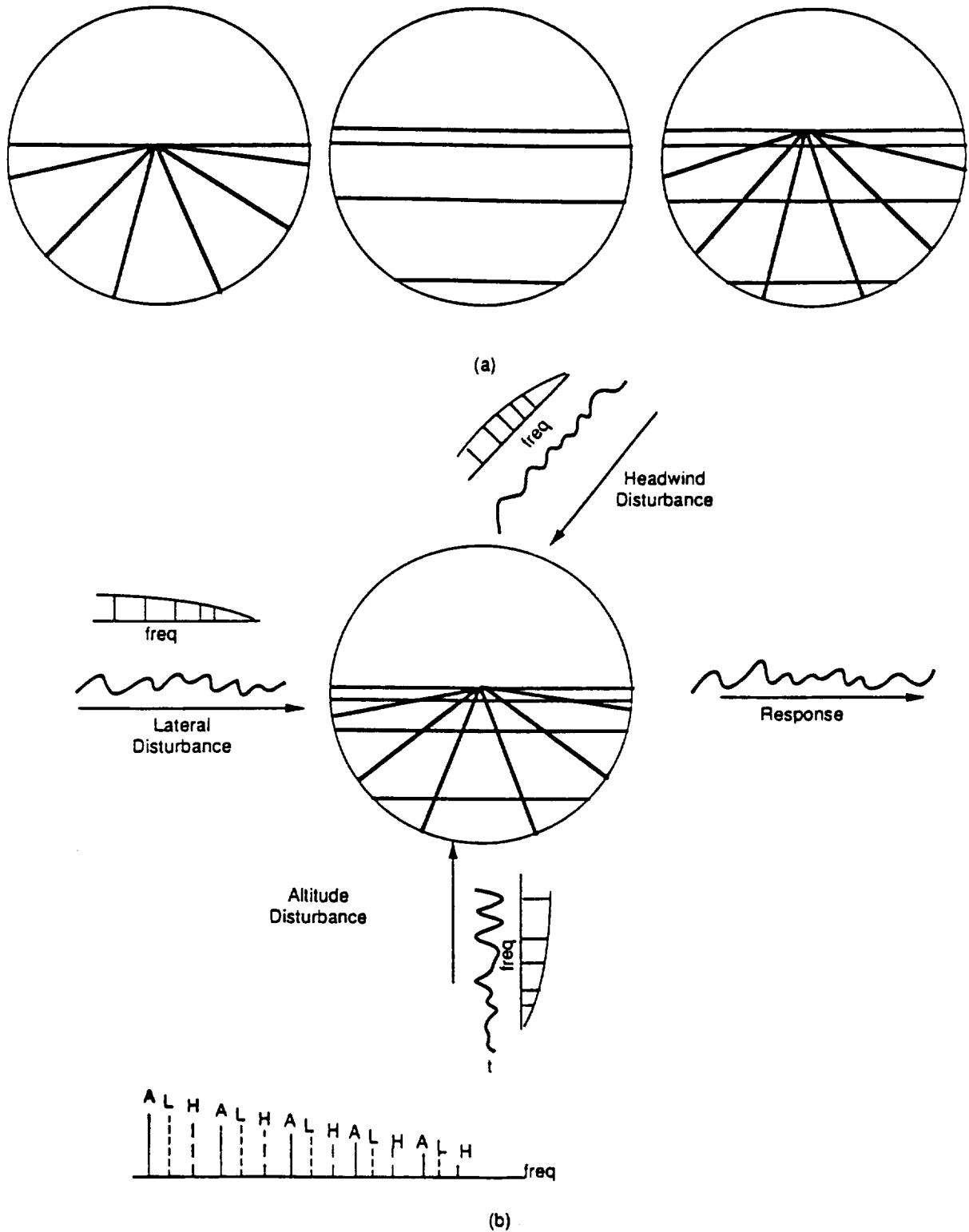


Figure 11. Illustrates logic of approach employed by Johnson et al. (1988) to evaluate alternative invariants for altitude control (A) Parallel (splay) texture, perpendicular (density) texture, and square texture (B) Frequency is used as a signature to isolate the effects of three disturbances (altitude, head wind, lateral) that were chosen because of their specific impacts on parallel and perpendicular texture.

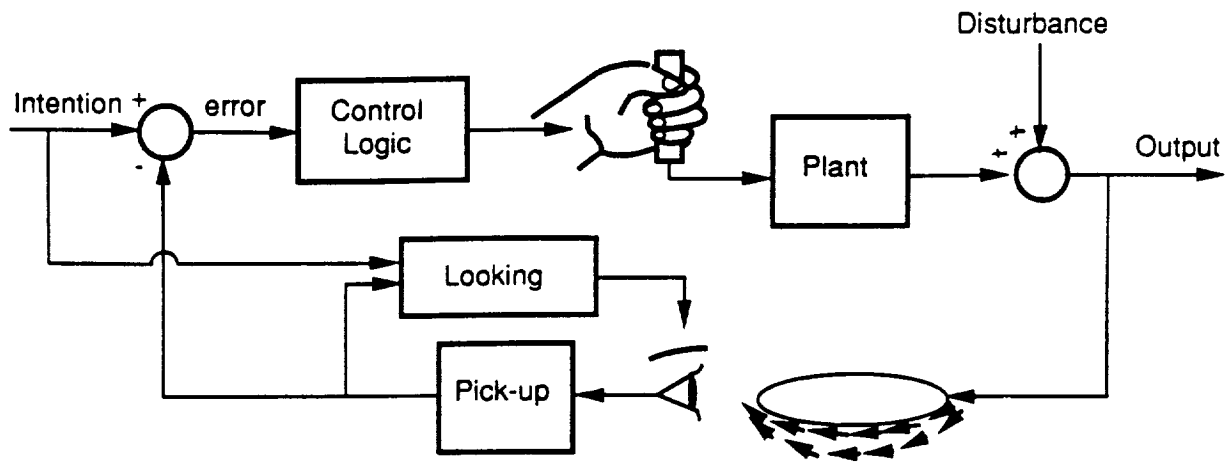
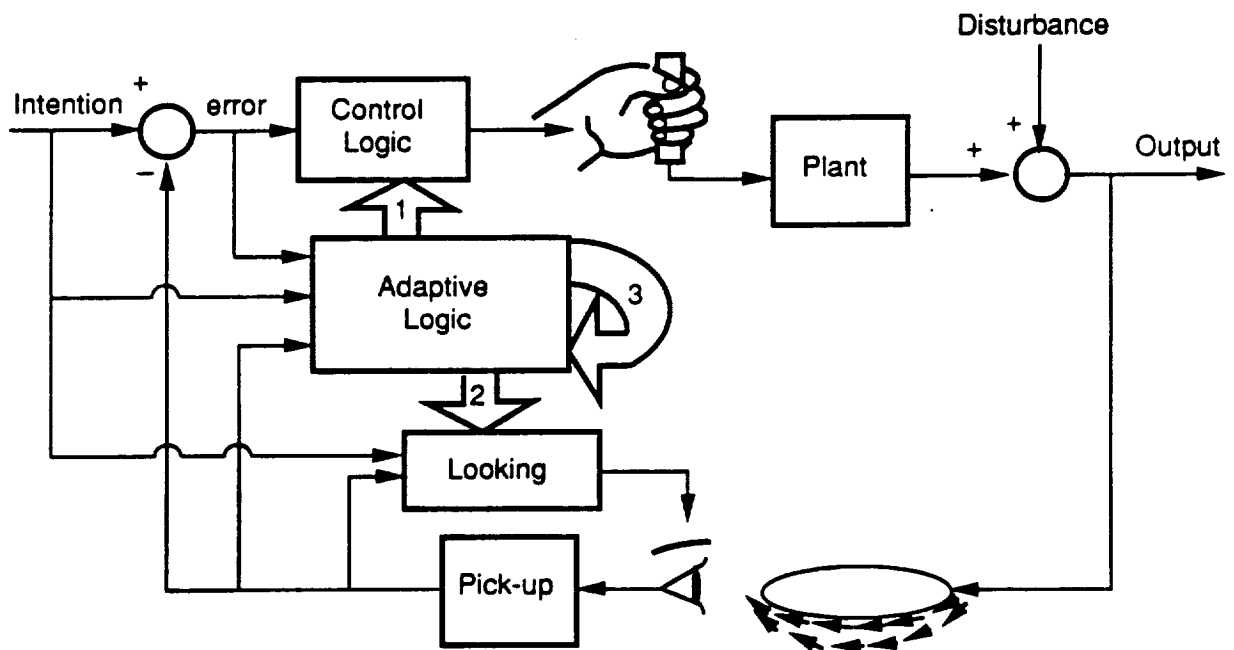
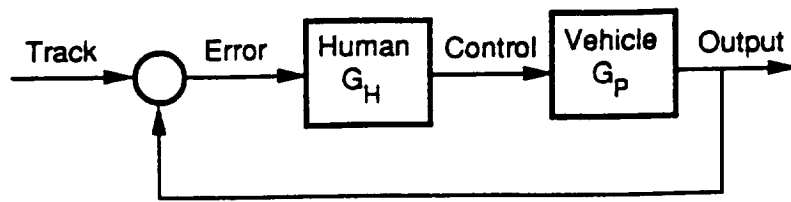


Figure 12. Uncoupling the eye (exploratory mode) from the hand (performatory mode).



1. Changing action strategies (motor learning)
2. Changing search strategies (discrimination learning)
3. Changing adaption strategies (learning to learn)

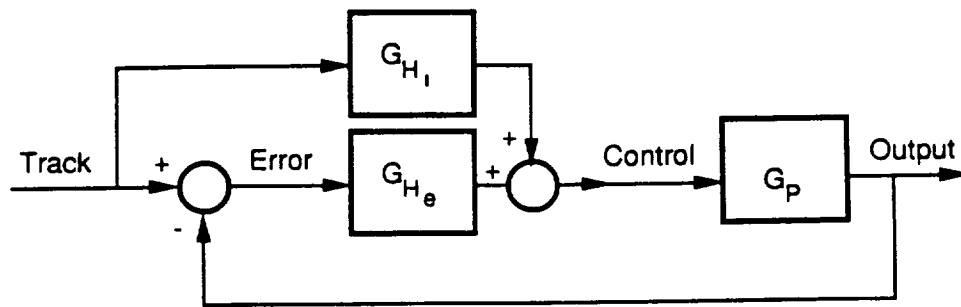
Figure 13. Adaptation—operating on operators.



$$\left[\frac{G_H G_P}{1 + G_H G_P} \right] \text{Input} = \text{Output}$$

Note: Match between input and output depends on open loop gain ($G_H G_P$)

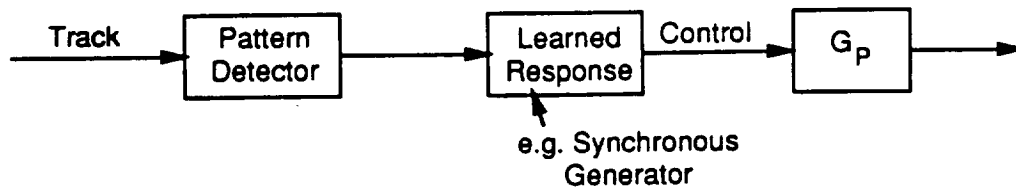
(a)



$$\left[\frac{G_P (G_{H_i} + G_{H_e})}{1 + G_{H_e} G_P} \right] \text{Input} = \text{Output}$$

Note: If $G_{H_i} = \frac{1}{G_P}$ (perfect mental model of plant), then input will equal output regardless of the open loop gain of the compensatory loop ($G_{H_e} G_P$)

(b)



Note: Open - loop control

(c)

Figure 14. The Successive Order of Perception model (SOP) proposed by McRuer et al. (1977) includes three control modes (a) compensatory, (b) pursuit, and (c) precognitive.